Developing a Fair Online Recruitment Framework Based on Job-seekers' Fairness Concerns

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The susceptibility to biases and discrimination is a pressing issue in today's labor markets. Though digital recruitment systems play an increasingly significant role in human resources management, thus far we lack a systematic understanding of human-centered design principles for fair online hiring. This work proposes a fair recruitment framework based on job-seekers' fairness concerns shared in an online forum. Through qualitative analysis, we uncover four overarching themes of job-seekers' fairness concerns, including discrimination against sensitive attributes, interaction biases, improper interpretations of qualifications, and power imbalance. Based on these findings, we derive design implications for algorithms and interfaces in recruitment systems, integrating them into a fair recruitment framework spanning different hiring stages and fairness considerations.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**.

Additional Key Words and Phrases: online recruitment, fairness, discrimination, online community, algorithm design

1 INTRODUCTION

Online recruitment plays an increasingly important role in human resource management. Digital hiring systems connect recruiters and job-seekers, and afford efficient sourcing, screening, assessment, selection, and hiring of candidates [17, 20, 36]. Online recruitment systems often embed automated tools to streamline the hiring process, such as customized job recommendations for job-seekers [48], or filtering and ranking interfaces to assist hiring decisions [17]. Therefore, online recruitment has been broadly adopted for its scalability and efficiency for recruiter-candidate matchmaking [17].

Despite the great potential of online recruitment, fair hiring remains a critical challenge in this process. There is rich evidence indicating that online recruitment tends to perpetuate or even amplify discrimination, biases, and imbalances inherent to offline hiring [28, 36, 47, 63, 72]. For example, Rao and Korolova found that in online job advertisements, companies tend to select images of candidates according to gender stereotypes for specific occupations, thus implicitly targeting or excluding people by gender [47].

Beyond replication of offline issues, the influence of *algorithms* and *interface designs* in the online setting poses new challenges to fair hiring. For instance, candidate ranking algorithms might be prone to outcomes favoring historically advantaged groups given the representation bias in the training sample [20], and job recommendation models might exhibit biases toward various demographic identities in recommended job types [63]. Regarding the interface design, a typical case is that the information provision for candidates at the subgroup level can increase discrimination [40]. Besides, social feedback interfaces might exacerbate biases to protected gender and race groups in

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the freelancing platform as they may receive worse reviews given equal qualifications, hindering their future work opportunities [28].

To confront biases in hiring algorithms, researchers in responsible computing have established diverse fairness measures for algorithm optimization (e.g., outcome fairness [29] and process fairness [27]), and developed pre-, in-, and post-processing approaches for bias mitigation [20, 35]. Regarding interface design for fair hiring, scholars in Human-Computer Interaction (HCI) and Computer-Supported Cooperative Work (CSCW) have investigated the design space to reduce human bias and assist fair decision-making, such as individual-level information provision [40] and AI-supported debiasing [18, 36].

While the research progress in fair online hiring is promising, the question of **whether the advancements in fairness research in online recruitment address the actual fairness concerns of job-seekers** remains pressing. In fact, recent research has highlighted the gap between idealized fair hiring models and the manifestations and perceptions of fairness in real life [9, 37, 65, 81]. Addressing biases through computational methods often leads to oversimplification, such as neglecting the intersectionality of social identities [20, 65]. Additionally, different notions of fairness may reflect fundamentally distinct worldviews [22], and specific operationalizations of fairness may not generalize across settings, potentially perpetuating inequality [65]. Moreover, fairness is not a binary concept [3]. Job applicants may perceive algorithmic recruitment as unfair, even when the outcome is favorable to them [37]. In some cases, this perception stems from concerns about systems failing to recognize candidates' uniqueness [37] or from a lack of transparency in decision-making [5]. Given these concerns, adopting a human-centered approach to fair hiring is crucial for translating real-world fairness challenges into implications for fair online hiring designs. It not only necessitates the refinement of *algorithm design* to better correspond to job-seekers' fairness needs, but also highlights the significance of *interface design* to enhance fairness perceptions beyond theoretical and computational fairness notions.

This work makes the first attempt to establish a fair online recruitment framework directly building upon job-seekers' fairness concerns. Specifically, we investigate the following questions:

- **RQ1**: Which fairness concerns are raised by job-seekers in online job communities?
- **RQ2**: How might job-seekers' fairness concerns translate into design insights for online hiring systems, in particular recruitment algorithms and interfaces?

For RQ1, we conduct a qualitative analysis of posts from r/jobs[1], one of the largest online job communities [24]. Our findings suggest four significant themes of job-seekers' fairness concerns, covering *discrimination against sensitive attributes*, *interaction bias*, *improper interpretations of qualifications*, and *power imbalance*. These fairness concerns capture a comprehensive overview of hiring challenges in the real world, shedding light on fairness perspectives that are noted by job-seekers yet potentially overlooked in the existing algorithmic fairness literature.

For RQ2, we propose how practitioners can translate the broad range of fairness considerations into concrete responsible system designs. Building upon the multifaceted fairness concerns identified in RQ1, We develop design implications for algorithms and interfaces in recruitment systems across different hiring stages in a comprehensive set of hiring scenarios. For example, we suggest enhancing *two-sided fairness* to cope with power asymmetry in job recommendation, and adopting *visual feature anonymization* to reduce biases due to visual proxies. We account for not only the limitations of online recruitment systems but also reflect on how to design interventions to alleviate biases perpetuated in offline hiring.

In summary, this work makes the following contributions to the HCI and responsible computing community: (1) we construct a comprehensive taxonomy of job-seekers' fairness concerns in hiring,

[1]https://www.reddit.com/r/jobs/

which forms the foundation of user-centered design for online hiring systems; (2) we establish a framework for designing fair recruitment *algorithms*, which situates algorithmic fairness to broader real-world fairness challenges; (3) we build a framework for designing fair recruitment *interfaces*, which aims to transit theoretical and computational fairness to fairness perceptions.

2 RELATED WORK

2.1 Understanding job-seekers' fairness concerns in online hiring

With the turbulent market and intense competition in today's economy, effective human resource management that aims to maximize candidate-job fit plays an irreplaceable role in business success [2, 54]. Unfortunately, though there has been great legal [14, 49], social [64, 67] and technical [20, 59] effort for fair and non-discriminatory hiring, job-seekers still hold broad fairness concerns when interacting with the recruitment ecosystem [36, 81]. Gaining insight into the fairness concerns of individual job seekers could illuminate strategies for integrating fairness-focused design into the hiring process.

With the advancement of hiring algorithms, HCI and responsible computing researchers have paid increasing attention to job-seekers' fairness concerns in the setting of automated hiring. For example, Zhang et al. found that the public generally has a negative attitude towards fairness in hiring algorithms [81]. Lavanchy et al. also noted that job applicants perceive algorithmic recruitment processes as less fair, regardless of whether the outcome is favorable to the applicant or not [37]. Such perceptions may vary according to the identity of job-seekers (e.g., more negative attitudes from women compared to men) and the type of algorithms (e.g., more negative attitudes towards video screening algorithms than resume screening algorithms) [81]. Some reasons for users' fairness concerns about algorithmic hiring include uncertainty of the current technology capability [36], worries about limited transparency in decision-making [5], and distrust of algorithms' ability to recognize their uniqueness as a candidate [37]. Corresponding to the gap between perceived job discrimination and actual job discrimination [3], these studies warn that despite the progress of outcome fairness of hiring algorithms [20, 73], it is important to critically reflect on more diverse dimensions of system and algorithm design to promote users' perceived fairness in automated hiring systems.

Moving a step further from just identifying existing limitations to improve recruitment systems and algorithms, this work takes a holistic view to unpack job-seekers' fairness perceptions: what fairness concerns do job-seekers disclose, and how do these fairness concerns shed light on the design of future hiring systems? Toward this goal, we situate this study in a natural setting, i.e., an online job community, to surface fairness concerns based on job-seekers' discourse. This attempt also corresponds to the principle of Value Sensitive Design (VSD) [23], deriving design implications for fair hiring systems through empirical investigations of job-seekers' fairness perceptions.

2.2 Designing algorithms for fair online hiring

Hiring algorithms have penetrated into different stages of human resource management. They span stages from *sourcing* to find potential candidates [48], *screening* to narrow down pools of applicants [19, 42], *selection* to optimize job offers [70], and *evaluation* after hiring [79]. As such, biases of hiring algorithms manifest in diverse patterns across different stages. For instance, Rao and Korolova noted that during job advertising, there was disproportionate representation or exclusion of certain demographics in job ad images, and ad delivery algorithm could amplify the skews [47]. Ranking algorithms employed by online recruitment platforms for candidate selection are also prone to a variety of undesirable biases (e.g., pro-male outcomes) [28, 72].

Facing such problems, HCI and responsible computing researchers have devoted significant attention to improving fairness in algorithmic hiring. First, the research community of fair hiring defined different dimensions of fairness measures for algorithm optimization, such as outcome fairness [29] (equal outcome in candidate predictions), accuracy fairness [7] (equal accuracy-related metrics between groups), and representation fairness [1] (stereotyping and biases in representations). Notably, most existing work takes group fairness as the primary objective, while individual fairness is still less adopted as a fairness criterion [20]. Recent research has also investigated process fairness by examining the predictability of sensitive attributes from non-sensitive ones [27]. Toward these fairness criteria, researchers develop different pre-, in-, and post-processing bias mitigation algorithms. For instance, Rule-based Removal [51] and Substitution [62] in pre-processing attempt to replace words that explicitly refer to sensitive attributes as the means to improving outcome fairness. With a similar intuition for proxy reduction, in-processing Adversarial Inference aims to reduce sensitive information in latent representation through additional adversarial loss [53]. DetGreedy is a typical example of post-processing, which greedily selects the most relevant candidate in the ranking while maintaining maximum and minimum representation constraints for each group [25].

While there have been extensive research efforts towards fair hiring algorithms, discrepancy still persists between algorithm development and real-world implementation. Limited datasets, characterized by issues like inadequate diversity and the absence of crucial sensitive attributes [20], pose a significant challenge to the generalizability of fair hiring algorithms. Besides, fair hiring algorithms often oversimplify the recruitment model, overlooking the interplay between different sensitive variables and the cascading effect across multiple hiring stages [35]. More importantly, due to a lack of model transparency, users often hold misperceptions of how algorithms work and distrust algorithm-based decision-making [9].

Following this line of work, our study aims to take a human-centered perspective to identify the potential gap between the advancement of fair hiring algorithms and users' fairness considerations in the hiring pipeline. Drawing insights from users' fairness perceptions, we reflect on what critical factors that future fair hiring algorithms should particularly pay attention to.

2.3 Designing interfaces for fair online hiring

As online recruitment is often powered by algorithms to afford automation and scalability, there is a vast literature on how algorithms inherit or amplify hiring discrimination [35]. The connection between hiring fairness and the interface design of recruitment systems, on the contrary, remains underexplored [40]. In fact, as a bridge between humans and algorithms in nearly every decision-making stage for both recruiters' and job-seekers' sides [40, 72], the interface design of recruitment systems can play a significant role in influencing (un)fair hiring decisions [40].

One strand of work in HCI and CSCW has delved into how the specific interface design of hiring systems is related to fairness and biases [11, 28, 40]. For example, Leung et al. found the provision of candidates' information at the individual level (performance of candidates in previous tasks) can significantly alleviate discrimination, yet the provision of information at the subgroup level (how the candidate's subgroup did in previous tasks) can increase discrimination [40]. In the setting of online freelancing, Hannák et al. found that biases against protected gender and race groups are exhibited through the social feedback interface, and suggested more selectively revealing review information to cope [28]. Affording accessible recruitment interfaces is another important component for fair hiring in a broad sense [4, 46, 74]. For instance, Wang et al. revealed how short video and live-streaming interfaces provide a user-friendly channel to aging job seekers [74].

Another thread of HCI and CSCW research particularly focuses on how to develop interfaces to facilitate fair hiring decisions for recruiters [18, 36, 80]. For instance, Lashkari and Cheng suggested that recruitment decision-making tools should support team collaboration that allows multiple roles to contribute to the decision process, and should also facilitate (e.g., summarizing candidate profiles) rather than perform decision-making [36]. Yang et al. developed and evaluated an AI system adopting fairness-aware machine learning to provide guidance on unbiased decision-making, illustrating its potential in prompting decision-makers to reflect on their biases and reassess fairness-related views [80].

This work contributes to this line of work by proposing a fair recruitment design framework based on job-seekers' fairness concerns. Integrating users' fairness concerns across diverse dimensions, this framework captures nuanced design considerations for both the interfaces of recruiters and job-seekers across different hiring stages.

3 METHOD

In this section, we describe our method to develop a fair online recruitment framework based on job-seekers' fairness concerns. We first introduce the data source and data collection method in Section 3.1. Then, we illustrate how we identified users' fairness concerns through qualitative analysis in Section 3.2, and developed design insights for online hiring systems to establish the framework in Section 3.3. We discuss the ethical considerations in Section 3.4.

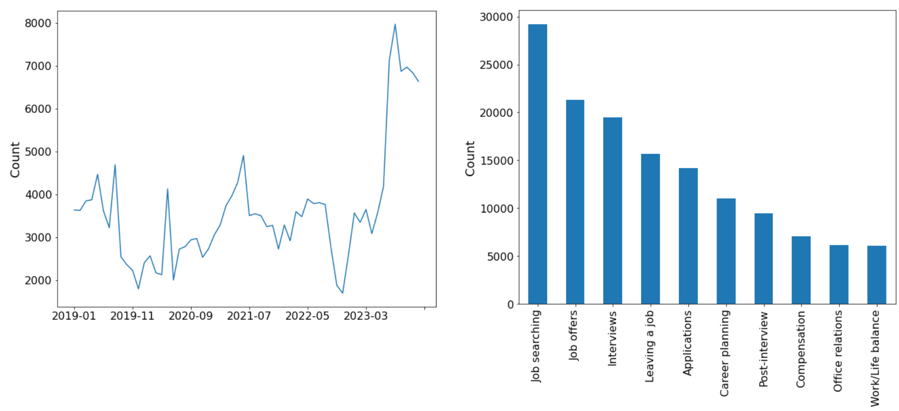
3.1 Data source and collection

To uncover job-seekers' general concerns about fairness in the recruitment process, we determined to turn to online job-seeking communities. This research setting can surface job-seekers' fairness concerns from a large and diverse group of community members in a natural setting. We did not choose company reviews or interview reviews in job-hunting apps such as Glassdoor or Indeed, as they mostly focus on specific stages in job applications (e.g., working/interview experience) and target particular companies, thus often lacking a general, systemic perspective on users' fairness perception. Similarly, we did not consider app reviews for job-hunting applications, as they mainly center on technical issues. Instead, our goal was to derive a fair recruitment framework based on not only existing technical limitations (i.e., how online recruitment systems might fail) but also broad fairness concerns in job-seeking (i.e., what online recruitment systems should consider).

3.1.1 Data source: r/jobs. To locate online communities where job-seekers gather to discuss fairness concerns in job hunting, we first broadly navigated popular social media platforms, including Twitter, Facebook, and Reddit, with relevant searching keywords (e.g., "hiring bias", "fair hiring" and "recruitment discrimination") in March 2024. We noticed that most posts on Twitter and Facebook public pages spread news in technology and law development on recruitment fairness, yet few shared personal experiences and concerns related to fairness during job seeking. Hence, we decided to focus the research platform specifically on Reddit, where extensive conversations revolved around fairness concerns as perceived by job-seekers and based on their experiences [24]. Though there were various subreddits discussing topics related to recruitment fairness, some particularly concentrated on specific stages in job hunting (e.g., "r/resumes" and "r/interviews" focusing on resume construction and job interviews separately), and some primarily centered around fairness-related discussions from the standpoint of recruiters rather than job-seekers' viewpoints (e.g., "r/recruiting" and "r/hiring"). Therefore, we finally located the subreddit "r/jobs", an online community that allowed general job-seekers to share opinions and experiences across different job-hunting stages.

The subreddit r/jobs, created in March 2008, is described as "the number one community for advice relating to your career"[2]. As of August 2024, r/jobs had 1.6 million members. The community forbids job posts or self-promotion of any kind. Instead, it encourages community members' sharing

[2] https://www.reddit.com/r/jobs/



(a) Temporal trend of the number of posts in r/jobs

(b) Number of the top 10 topics in r/jobs

Fig. 1. Descriptive statistics on (a) temporal trend and (b) topic distribution of posts in r/jobs. The count in the y-axis indicates the number of posts in the corresponding month(s) for figure (a) and the number of posts with relevant tags for figure (b).

of advice related to its core mission - supporting "how to get a job" or "how to quit a job". The community affords broad topics of "flairs" to tag each post, covering "Job Searching", "Applications", "Resumes/CVs", "Interviews", "Job offers", "Leaving a job" and so on. Without any specific limitations of job-seeking stages or topics, r/jobs provides a community where job-seekers can exchange a wide range of experiences and opinions, including those relevant to hiring fairness.

3.1.2 Data collection and preprocessing. Due to the API restriction for data collection on Reddit since 2023 [78], we adopted the Reddit dump files contributed by the r/pushshift community [69]. We first collected and extracted all the posts (N=388,108) from r/jobs in the past five years (2019-2023). Then, we removed all posts with "deleted" or "removed" status, leading to 216,441 post submissions. The metadata of posts included *id, post title, post description, created timestamp, hashtag*, and *number of comments, views, and votes (ups/downs)*. The temporal trend and topic distributions of posts in r/jobs are shown in Figure 1.

3.2 RQ1: Identifying users' fairness concerns

3.2.1 Conceptualizing fairness. Considering the complexity of fairness, we grounded our evaluation of *whether a post contains users' fairness concerns* in the theoretical framework proposed by Colquitt and Rodell [12]. It posed a broad definition of "fairness", which aligned with our research goal to surface a comprehensive taxonomy of users' fairness concerns. According to this framework [12], a post could be included for analysis if it was related to any of the following four facets of the job-seeking process: (1) procedural fairness, i.e., the fairness perceived in the procedures used to make decisions; (2) distributive fairness, i.e., perceived fairness of outcomes; (3) interpersonal fairness, i.e., the perception of fairness in interpersonal treatment and interactions; (4) informational fairness, i.e., the transparency and adequacy of information during decision-making processes. This data inclusion criterion helps us to locate posts reflecting job-seekers' various fairness concerns, building the foundation for further analysis.

3.2.2 Classifying Fairness-related Posts. Through an exploratory step navigating the dataset for familiarization, we observed that the r/jobs community covered miscellaneous topics about seeking or quitting a job, thus a random sample might contained a low proportion of posts related to fairness concerns in job-seeking. Therefore, we leveraged text classification to establish a valid dataset for qualitative analysis.

Sampling. Considering the relatively small fraction of fairness-related posts in the dataset, we took a strategic sampling approach to construct the training sample, combining 500 random posts from *the whole dataset* and 500 posts randomly selected from *a keyword-filtered subset*. In particular, we incorporated a post into the subset if it contained any of the following keywords about fairness: *bias(ed), discriminat(e/ion), prejudice(d), stereotype, (un)fair(ness), (im)partial(ity), (in/un)equal(lity).* Note that these keywords can neither ensure the inclusiveness and purity of the keyword-filtered subset: many posts expressed fairness concerns with plain language rather than framing them as the "fairness" issue, and posts containing these keywords may touch on other topics (e.g., office relations). Therefore, the keyword-filtered subset only served for preparing a dataset with a high proportion of samples related to the research focus, instead of being treated as the ground truth of estimating fairness concerns. On the other hand, as the keywords might constrain the topics in the keyword-filtered subset, the 500 random posts helped to mitigate the potential missing themes about fairness concerns. It finally leads to 1000 posts for annotation.

Annotation. We manually annotated the sample to assign a binary label to each post, i.e., whether it was related to users' fairness concerns in job-seeking or not. After conceptualizing fairness, we established the criteria for annotation: a post was labeled as positive if (1) it touched on any of the facets of *procedural, distributive, interpersonal* and *informational* fairness [12]; (2) it focused on the fairness in the hiring process, e.g, posts criticizing discrimination in the office were excluded. Two researchers first conducted individual coding on the initial 100 samples. The Cohen's Kappa (a statistical measure to quantify inter-rater reliability) [45] reached 0.93, suggesting substantial agreement between the two coders. Then, the two coders took multiple rounds of discussions to reconcile discrepancies. Finally, the authors individually annotated an additional set of 450 posts each, resulting in a total of 1000 labeled samples.

Model training. We fine-tuned RoBERTa, a variant of the BERT (Bidirectional Encoder Representations from Transformers), as the base model for our specific task considering its effective contextual embedding for text classification [43]. We divided the 1000 labeled samples into training, validation, and testing sets using an 8:1:1 ratio, and concatenated the post title and description as the text input. Given the limited sample size for fine-tuning, we adopted a dropout rate of 0.2, and employed early stopping to prevent overfitting. The text classification achieved good performance with the F1-score = 82.0% on the test set. We applied the classifier to assign the label of *relating to job-seekers' fairness concerns in hiring or not* for all 216,441 r/jobs posts in our dataset. The text classification yielded 28,567 posts reflecting job-seekers' fairness concerns in hiring, accounting for 13.2% of the whole dataset.

3.2.3 Analyzing fairness concerns. The text classification prepared the subset for qualitatively analyzing users' fairness concerns. To inductively capture the fairness concerns raised by job-seekers, we employed a grounded theory approach [13] to analyze the data. This allowed the codes to naturally surface during the analysis process. First, two authors adopted open coding [13] to individually analyze 200 samples to generate initial codes. The two coders subsequently engaged in multiple rounds of meetings, comparisons, and discussions to establish a consensus on the codebook[3]. Examples of codes included "*bias in the communication method*" and "*prejudice related to working history*". Subsequently, the two authors iteratively revisited the data, applied the established

[3]In the coding process, we excluded the misclassified posts when the coders encountered them to ensure the validity of the codebook.

codes to additional posts, and documented any newly emerging codes. The coding phase concluded when no further new codes surfaced. Following this iterative coding process, the two authors coded 670 posts in total. Finally, the two coders utilized axial coding [13] to categorize the codes and merge similar ones into overarching themes, such as merging "*bias in the communication method*", "*bias in the self-presentation approach*" and some other relevant codes to the theme "*interaction bias*". The two authors finally analyzed 100 additional posts based on the final codebook and no new codes emerged, validating that the coding reached saturation.

3.3 RQ2: Developing design insights for online hiring systems

Based on the taxonomy of job-seekers' fairness concerns, we developed design insights for online hiring systems. This process followed principles of Value Sensitive Design [23], which emphasizes proactively integrating human values (fairness in this work) into the design of technology. Specifically, two authors who were experienced in hiring fairness first went through the findings of RQ1, deepening the understanding of job-seekers' needs and concerns regarding recruitment fairness, as a process of *empirical investigation* [23]. They situated the findings within the existing literature about the algorithm and interface design for fair hiring for *conceptual investigation* [23], reflecting on how fairness as a value interacts with this sociotechnical system. Next, with *technical investigation* [23] in mind, they connected fairness with different technical components in the recruitment system, and derived design insights particularly based on (1) how these fairness concerns might influence the development of online hiring systems and (2) how online hiring systems can be improved to address relevant fairness issues through algorithm and interface design. The insights were refined through several rounds of meetings and discussions. Finally, they contextualized the design insights within the hiring ecosystem by connecting the implications to the relevant stage or component of the hiring pipeline to achieve *contextual integration* [23]. This process helped to develop the framework for designing fair hiring algorithms and interfaces, respectively.

3.4 Ethical considerations

As a secondary analysis of publicly available data, we established our study's eligibility for self-exemption under our Institutional Review Board (IRB)'s guidelines. However, we recognized that IRB guidelines may not always suffice for community safety [55] and our research topic may involve controversial posts. Therefore, we implemented various protective measures to safeguard the privacy and security of the studied Reddit community. First, the collected data were securely stored on a password-protected computer accessible solely to the research team. Second, we paraphrased all quoted posts instead of using direct quotes, preventing traceability to original posts. Furthermore, real usernames or user IDs were not incorporated in the paper to protect the identities of community members. Finally, we ensured no direct engagement with human subjects, such as responding to posts or interacting with community members. These precautions help to minimize risks to the community.

4 FINDINGS AND IMPLICATIONS

The qualitative analysis of r/jobs posts revealed a comprehensive taxonomy of job-seekers' fairness concerns (RQ1). It covers four overarching themes, including *discrimination against sensitive attributes* in Section 4.1, *interaction bias* in Section 4.2, *improper interpretations of qualifications* in Section 4.3, and *power imbalance* in Section 4.4. For each theme, we situate users' fairness concerns within the existing literature on fair hiring algorithms and designs, and provide design insights for online hiring systems accordingly (RQ2).

4.1 Discrimination against sensitive attributes

Discrimination against individuals based on sensitive attributes, such as race, gender, sexual orientation, religion and disability status, is broadly documented in the existing literature on hiring and job market [34, 56, 57, 60]. Our qualitative analysis also manifested users' fairness concerns about these personal characteristics in many ways. The fairness concerns, along with the code descriptions and (paraphrased) examples, were presented in Table 1.

In general, job-seekers' fairness concerns about sensitive attributes spanned all stages in the hiring pipeline, from sourcing, through CV screening, to candidate evaluation. Notably, in addition to well-documented protected attributes such as race and gender [33, 72], we identified some factors that were less highlighted in fair recruitment algorithms, although users have expressed extensive concerns about them. For example, job-seekers expressed worries regarding the influence of *appearance bias* in recruitment, such as how hairstyle, facial hair style, and dress style may bring discriminatory negative impressions in their CVs, recorded video presentations, and interviews. Also, *family bias* has been raised by some job-seekers when they believed their marriage and children contributed to the job rejection, especially when interconnected with age and gender (e.g., discrimination against single moms). *Geolocation bias* has also been widely noted regarding the discrimination against non-local job-seekers and candidates from specific areas. These factors indicate the complexity and diversity of discrimination against sensitive attributes. Besides, the findings uncovered that bias towards sensitive attributes was not always based on job-seekers' direct personal disclosure; rather, they were often indirectly inferred from individuals' relevant experiences and characteristics (as proxy attributes [82]), such as inferring age from education and working background, and inferring race and gender from job-seekers' name. Finally, our findings revealed that sensitive attributes often intertwined with each other, such as the inherent connection of appearance with age, race, and gender.

4.1.1 Design Implications.

Incorporating more diverse sensitive attributes and stages into the fair recruitment systems. Mainstream fair hiring algorithms mostly focus on the sourcing and screening stages (e.g., job recommendation and CV ranking) [41], and pay attention to specific subsets of sensitive attributes (e.g., race and gender) [20, 33, 72]. The available datasets for algorithmic fairness research also exhibit corresponding imbalances in sensitive attributes and stages. For example, a recent survey on fairness in algorithmic hiring revealed that existing datasets for fair hiring research had limited dimensions of sensitive variables, and largely focused on gender and race/ethnicity [20]. Nonetheless, we find that users' fairness concerns are multi-faceted. Factors such as appearance bias, disability bias, and location bias, though less covered in fair hiring research and datasets, are widely complained by job-seekers. Some bias factors also strongly affect the late stages of the hiring pipeline instead of sourcing and screening, e.g., appearance bias influencing interviews and health bias influencing background checks. Therefore, we suggest researchers and industry practitioners actively **include diverse bias factors and hiring stages (D1.1)**[4] when building fair recruitment systems. In particular, when existing datasets cover limited features to train and evaluate fair hiring algorithms, it shows great potential to organize **data donation campaigns (D1.2)** with informed consent [26] to establish datasets with expanded dimensions of sensitive attributes for fair hiring research.

Proxy mitigation for sensitive attributes within fair recruitment systems. The findings highlight the *implicitness* of sensitive attributes with broad proxy characteristics existing in the hiring process.

[4] We use "D" to denote Design insights/considerations.

Table 1. Discrimination against sensitive attributes.

Fairness Concern	Description	Example
ageism	Bias based on age. Often inferred from education and working experience, appearance, and future plans	*I've been facing discrimination for the past year. Everywhere I apply, they tend to hire younger candidates, most of whom have no experience. It makes me feel like our experience doesn't hold any value.*
sexism	Bias based on being perceived as male or female, and relevant stereotypes of gender roles. Can be direct or indirect (e.g., pregnancy and children); Manifested in both outcome fairness and procedural fairness (e.g., additional formalities)	*Would it be dishonest to use a gender-neutral name on my resume to avoid potential gender bias? The field I'm pursuing is male-dominated, and I want to prevent any assumptions about me based on my gender.*
LGBTQ+ bias	Bias against LGBTQ+ individuals. Often intersect with appearance bias.	*I faced another rejection, and I'm slowly becoming accustomed to it. I'm transgender, which unfortunately led to various biases from the hiring team.*
ethnicity/nationality bias	Bias based on ethnicity and nationality. Often inferred from name and language; Manifested in both outcome fairness and procedural fairness	*I've heard that employers often subconsciously discriminate based on names when reviewing applications. In general, the less foreign-sounding your name is, the better your chances are of getting a callback.*
appearance bias	Bias based on appearance. Taking effect in diverse stages (e.g., CV and interview); often intersectional (e.g., with ageism and sexism)	*As a woman with a "boy cut" hairstyle, I've heard from others that some HR professionals may discriminate against this, favoring candidates who appear more "normal".*
disability/health bias	Bias based on disability and health conditions. Nuanced differences in visible/non-visible and mental/physical conditions.	*I was just denied a job because I'm unvaccinated due to medical reasons. Is this legal, and do I have grounds to sue for discrimination or wrongful rejection?*
geolocation bias	Bias based on geolocation, such as discrimination against non-local job-seekers and individuals from specific areas.	*Unlike back home, I'm only getting a 1%-5% response rate. I'm fairly certain I'm facing discrimination based on my location*
family bias	Bias based on family issues such as marriage, pregnancy, children, etc.	*In an ideal world, there would be no discrimination against mothers or single moms in the workplace. Do you think it's unwise to mention being a mom or single mom during job interviews?*
political bias	Bias based on political affiliation.	*I work in tech and I'm a U.S. military veteran. Since military vets tend to be more conservative than the general population, I'm concerned that it's becoming a red flag. Recently, several big-name companies have rejected my resume.*
religion bias	Bias based on religious beliefs.	*I'm feeling nervous that if they invite me for an interview, they might bring up questions about whether I'm Christian. I understand this would be discriminatory if they base hiring decisions on that, but a business could easily justify it by saying, 'You are just not experienced enough.'*

Typical examples include inferring age from education and working background, inferring ethnicity from the name, inferring geolocation from contact information, and inferring family status from social media background checks. These findings echo prior work that called for the investigation of process fairness to achieve outcome fairness in hiring, which necessitates the measurement of predictability of sensitive variables from non-sensitive ones [31]. Besides, the implicitness of sensitive attributes warns of the vulnerability of some pre-processing approaches for fair hiring algorithms that mainly consider explicit variables. For example, either rule-based scraping [16] (automatically removing words related to sensitive attributes) and rule-based substitution [62] (automatically neutralizing all words related to sensitive attributes) may fail to fundamentally present a debiased resume. Designers of hiring algorithms and systems are suggested to critically reflect on **proxy mitigation (D1.3)**, i.e., how to avoid commonly believed non-sensitive qualifications from being leveraged as proxies for protected sensitive attributes. Toward this goal, this work illustrates rich nuances of how proxy attributes manifest in hiring systems based on job-seekers' understanding and disclosure. Investigating how recruiters identify, perceive, and utilize proxy attributes is warranted to further supplement the understanding of the roles of proxy attributes and possible mitigation ways.

Besides, considering the prevalence of proxy variables, we also suggest policymakers **regulate the information request (D1.4)** in hiring systems as a basic approach to alleviate proxy-based discrimination. In particular, before the adoption of specific hiring systems, it is necessary to scrutinize whether specific requested information is significant for qualification assessment, or suspicious as a proxy susceptible to discrimination. For example, when proposing the interface requesting education background, is it necessary to ask for the year of graduation? Is it necessary to ask for photos or videos fraught with proxies? Such protection of proxy attributes corresponds to *indirect discrimination* in European non-discrimination law [49] and *disparate impact* in US non-discrimination law [14], both highlighting the discrimination when the practice is seemingly neutral but ends up discriminating against disadvantaged groups.

Handling visual data. The findings suggest that some user-perceived biases are more visual-related (e.g., appearance and disability bias) based on photos, recorded videos or synchronous interviews, which challenges the practicality of traditional debiasing approaches primarily relying on text and tabular data. Therefore, it is crucial for researchers and developers of fair hiring to critically reflect on the debiasing in the multimodal setting. In particular, we propose a standardized pipeline for processing visual and video data. First, as photos and videos can be fraught with proxies, it might be beneficial to adopt a nudge interface prompting companies to deliberate on the necessity (i.e., **visual feature consideration (D1.5)**): do you really need to collect personal photos or recorded videos from candidates? Second, if the company does require visual and video data, hiring systems can encourage the use of a virtual avatar system for videos or synchronous interviews that can remove most proxies (i.e., **visual feature masking (D1.6)**) [6, 15]. Further, for settings where avatars don't work, hiring systems may afford preprocessing elements to neutralize or hide visual-based sensitive attributes (i.e., **visual feature neutralization (D1.7)**), such as adopting algorithms for face decorrelation [32]. Nonetheless, it is warranted for future research to examine the tension between the effectiveness of visual debiasing and the validity of evaluation (e.g., the correlation with trust and proximity).

Measuring input fairness. Current fairness measures mostly focus on acceptance rates for applicants with protected identities. According to a popular definition of fairness grounded in disparate impact doctrine, a system with 10 male and 2 female applicants can be considered fair if it hires 5 men and 1 woman [20]. This fairness definition is narrow since it takes for granted the composition of applicant pools and only focuses on algorithmic outcomes. The prominent status of outcome fairness entails a lack of incentives for system-wide scrutiny. Indeed, it is imperative to also measure and counter the underrepresentation of protected identities among applicants, which is often due to structural biases. **Measuring input fairness (D1.8)** as part of a system evaluation, i.e. analyzing the composition of applicant pools, can surface problematic aspects of the broader hiring system, including discouraging effects of non-inclusive interfaces.

4.2 Interaction bias

We identified job-seekers' nuanced fairness concerns during the interactions with hiring systems and companies, as shown in Table 2. They cover all stages in the hiring process that involve applicant-system and applicant-recruiter interaction, from how job-seekers get in touch with the company, present themselves in resume and hiring systems, coordinate and schedule interviews, to how job-seekers propose post-interview questions. Job-seekers believed that recruiters were very likely to form possibly biased impressions during the interaction, and intentionally or unintentionally make

Table 2. Interaction bias

Fairness Concern	Description	Example
communication method	Bias based on how job applicants connect with the company, e.g., mail vs. email, private channels vs. public channels, company websites vs. recruitment tools, etc.	*Every job I've been hired for came through a paper application, never online. It's frustrating because online applications always seem to go nowhere, but when I look for places that accept paper applications, I usually get a couple of responses.*
self-presentation approach	Bias based on how job applicants present themselves, e.g., the structure and font of resume, the design of the personal website, etc.	*I was rejected by every company I applied to. What did I do wrong?... I designed a more visually appealing resume instead of using the typical Times New Roman font... My dad advised me not to make it overly artistic, but I didn't listen.*
interview process	Bias based on how interview happens, e.g., the time, sequence, availability and time difference of interview	*Hiring managers are often more alert and focused at the start of the hiring process, which can make the first interviewee more memorable.*
evaluation method	Bias based on how evaluation works, e.g., unsuitable evaluation systems and unreasonable interview questions	*I just took the WonScore test, and it was terrible! I expected a few "personality" questions, but instead, I had to complete an IQ test, write 3 short essays, and answer over 200 personality questions. On top of being overly tedious, the test asked discriminatory questions and gave off a very ableist and classist vibe.*
technical issue	Limitations of the technical systems that may bring unequal outcomes, e.g., universities not in the database	*It's frustrating because I'm great at phone interviews and often highly qualified, yet I miss out on opportunities due to a flawed system.*
opt-out decision	Opt-out decisions that may influence impression, e.g., opt-out AI evaluation and sensitive identity disclosure	*I understand it's labeled as voluntary, but does it impact my chances? I know the HR personnel don't see the specific details I provide for race, gender, military status, etc., but will they know whether I answered at all? ...Could they make assumptions or hold biases about my decision not to complete it?*
questions and feedback	Bias based on whether and how job-seekers raise questions on/off-interview	*I have an interview next week that includes a technical portion. I asked what format the technical part will take, and now I'm wondering if I've already hurt my chances by asking, as it might seem like I'm trying to gain an unfair advantage.*

hiring decisions based on them. These fairness concerns are mostly related to the level of *individual fairness* in hiring [30], i.e. similarly qualified candidates receive comparable outcomes without discrimination based on irrelevant traits. Compared to group fairness, individual fairness has gained much less attention from researchers and developers for (algorithmic) hiring systems [30].

4.2.1 Design Implications.

Nudges toward objective evaluation. The interaction bias highlights a significant challenge in the hiring decision-making process: recruiters' evaluations might be influenced by recruiter-candidate interactions, which can sometimes deviate from objectively measuring individual qualifications. For example, individuals' communication or self-presentation approaches might fail to meet recruiters' personal preferences, and further become the source of biased hiring decisions. To this end, it is warranted to develop and examine design approaches to support recruiters in making impartial decisions that are minimally influenced by irrelevant individual interactions. In particular, **nudges toward objective evaluation (D2.1)**, suggesting recruiters reflect on the rationale of candidate selection or rejection, might facilitate more rational and transparent hiring. Such nudges can also be empowered by AI to make more customized rectifications [80]. Notably, nudges toward objective evaluation may not only apply to real-world recruiters' decision-making, but also be a potentially valuable practice for data annotation. For example, nudging annotators to score CV more based on qualifications instead of being influenced by CV structure and font, might be helpful to create a more quality dataset to build fair hiring algorithms.

Standardization of hiring pipeline to promote perceived fairness. The job-seekers' concerns about interaction bias reflected the potential limitations when recruiter-candidate interactions are taken as (inaccurate) proxies for qualification evaluations, which brings opacity to the hiring process. Notably, users did not (and cannot) raise direct evidence of the existence of interaction bias: job-seekers' concerns of interaction bias often manifest in a preconceived (i.e., assuming specific interaction patterns would bring disadvantages in job-hunting) or attributed (i.e., attributing the failure of job applications to particular interactions) manner. In other words, there is the possibility of misattribution [76, 77] when users perceive the influence of interactions: even in cases when irrelevant recruiter-candidate interactions do not actually influence qualification evaluation and decision-making, the uncertainty and ambiguity of interactions would amplify the distrust of process fairness. It enlightens a promising design direction: standardizing the hiring pipeline. Specifically, we highlight two critical components: **modularization and transparentization of the hiring pipeline (D2.2)**. First, modularizing the hiring pipeline could play a pivotal role in minimizing the transfer of irrelevant information across hiring stages, reducing the influence of unrelated interactions on decision-making. For instance, separating the modules of CV collection and candidate evaluation could reduce the impact of communication channels on candidate selection. Also, adopting the module of CV parsing and anonymizing before qualification assessment could reduce the influence of CV structure and design if it is irrelevant to employment duties. After modularization, transparentizing the modules, including informing users on how hiring tools are modularized and which stakeholders are involved in each module, would be important to improve perceived fairness. For example, informing candidates that the selection of interview time and opt-out decisions would not be visible to recruitment evaluators in the hiring systems might be beneficial to enhance the perceived process fairness for job-seekers.

Affording accessible interfaces for diverse identities. Another significant finding in interaction bias is that specific interactions are related to job-seekers' backgrounds, which could amplify the disadvantages of some marginalized groups. For instance, individuals with education experience in the Global South might not find their universities in the database of hiring systems as an unexpected technical issue. Similarly, candidates with speech impairment would find the fixed-time self-presentation insufficient to present themselves. To this end, we suggest **accessible interfaces for diverse identities (D2.3)**. First, allowing for exceptions of input would provide a basic level of inclusion in computer-mediated hiring systems. Hiring systems are recommended to support individuals with **flexible input for exceptional information (D2.4)** (e.g., options of open text to input education and working background) when some features exclude or marginalize specific groups. To avoid discriminatory treatment for exceptions, involving human-AI collaboration might be a feasible approach to integrate exceptional information seamlessly. Moving a step further, it is important for designers of hiring systems to identify nuanced interaction challenges for specific marginalized groups, and actively develop specialized interfaces to afford accessibility to them. For example, with the research advancement of accessible video conferencing [39, 61], HCI researchers and practitioners are suggested to embed relevant design guidelines into the specialized video interviewing systems for underrepresented groups (e.g., users with hearing, speech, or visual impairment).

4.3 Improper interpretations of qualifications

Table 3 demonstrates how job-seekers raised fairness concerns about improper interpretations of qualifications in the hiring process. It covers various non-protected factors, including *education*, *working history*, *reference*, *personality*, and *background blemish*. Job-seekers' fairness concerns about improper interpretations of qualifications mainly lie in two levels. First, some job-seekers

Table 3. Improper interpretations of qualifications

Fairness Concern	Description	Example
education	The education level, region, school, and department may inherit social inequality and may not well correspond to the necessary skills required for a job.	*I graduated from university two years ago with a degree in business administration from a third-world country. My diploma meets Western education standards, but since moving back to Scandinavia, I've been struggling to enter the job market. Employers seem incredibly biased, and I'm having a hard time even securing phone interviews.*
working history	Working history may be influenced by personal decisions (e.g., health conditions leading to short-term work and job gaps) and working environment (e.g., discrimination in the workplace leading to job leave), both related to social inequality.	*I left my previous job after 9 months due to a toxic work environment and inconsistent training, which led to frequent reprimands and double standards. How should I answer if asked about my reason for leaving? Should I be honest or give a different explanation?*
reference	References/recommendation letters reflect individuals' social capital, which might inherit social inequality, workplace prejudice, and disputes over interests.	*I've technically been hired, but they still need to check my three references. I'm a bit nervous that my current employer might say something negative out of spite, since I'm one of their best employees and my leaving would put them in a tough spot.*
personality	Personality (e.g., being introvert or extrovert), often shaped by the social environment, may influence hiring decision-making but not well represent qualifications.	*I've been job hunting for almost two years now, and I'm starting to realize that as an extreme introvert, it feels nearly impossible to get hired unless I act extroverted. It's frustrating, and I'm growing increasingly resentful of hiring managers because of it.*
background blemish	Background blemish (e.g., criminal record), fundamentally influencing background checks, may inherit societal prejudice.	*I'm identified as Black and had a strangulation and suffocation charge dismissed because the person who accused me lied and didn't want to continue with the trial... These incidents shouldn't be considered, not only because they didn't happen but also because the charges were dropped. Could I be discriminated against because of this?*

noted that these qualifications perpetuated social disparity in many ways. For instance, social stratification results in variations in educational background and referral letters for individuals with similar skills; discrimination in the workplace might lead to job leave that is difficult to explain to future employers; marginalized groups might experience unfair treatment in social life that disadvantages the background check. In addition, some job-seekers held concerns that these non-protected factors sometimes exhibit low correlations with required skills for a position, while serving as a symbol of social identity instead. These fairness concerns underscore how seemingly reasonable qualifications can inherit social inequality and further impose limitations on underprivileged communities. The indirect production of discrimination exhibits the social construction of inequality [50], necessitating the development of fair hiring systems within the social context.

4.3.1 Design Implications.

Investigating indirect bias. The findings signify that institutional biases can be inherited, accumulated, and reinforced across life stages. For example, discrimination in previous workplaces can lead to job leave with poor recommendation letters, which might further contribute to difficulty in job hunting and long work gap, eventually developing unfavorable conditions for job-seeking. Though less perceptible compared to direct discrimination based on sensitive attributes, such indirect bias has become a challenge to hiring systems that is difficult to eradicate. Different from the protected attributes such as race and gender, it is less possible to remove or neutralize qualifications like educational background and working history, as these components are also significant factors in evaluation. To this end, some scholars have realized the indirect bias due to the underlying inequality between different groups regarding qualifications, and developed countermeasures to cope with it. For example, Booth et al. proposed group normalization as a bias mitigation strategy, dividing job-seekers' data based on their sensitive group membership and normalizing each feature within the group [8]. Nonetheless, this method still neglects the intersectionality of sensitive attributes and retains the possibility of intra-group discrimination [8]. Therefore, we call for more study **investigating indirect bias (D3.1)** when establishing fair ranking algorithms. One possible solution is to prioritize the skills and abilities (e.g., programming expertise) and reduce the weight of indirect measures (e.g., educational background) for specific job recruitment. Besides, algorithm developers may consider the correlations of protected attributes and qualifications for calibration, reducing the influence of accumulated (dis)advantage. Besides, the indirect bias also highlights the significance of **establishing objective target variables (D3.2)** in model development, such as taking skill and experience relevance as the primary target variable instead of measures like similarity to past employees.

Performing careful variable selections at a nuanced level. The findings indicate that outwardly proper qualifications can have improper components that are more likely to conduce to biases. For example, work experience is a benign factor overall, yet the work gap can sometimes be a problematic feature prone to bias. Similarly, educational background is important information to know a candidate, yet the university and major might bring subjective and preconceived perspectives in some scenarios. Therefore, we suggest performing **nuanced variable selections (D3.3)** to facilitate fair recruitment. To begin with, we suggest algorithm designers develop a pre-processing component to discern fine-grained features, creating space for subsequent anonymization of specific child features. For example, when parsing the raw text of work experience in a CV, it shows the potential to adopt Named Entity Recognition to identify elements (job title, company name, duration, responsibilities, etc.), and then carefully determine the fine-grained variables as the input for fair recruitment algorithms, discarding some inappropriate features based on specific fair hiring considerations (e.g., removing work gap).

Supporting the right to be a data-driven exception. Job-seekers' fairness concerns about background blemish in Section 4.3 suggest that societal prejudice can sometimes contribute to the generation and amplification of individuals' serious background problems (e.g., possibly inaccurate criminal records), which have lasting consequences and fundamentally limit the job opportunity for the individual involved. Similar cases also include the lost education opportunities and the long employment gap due to institutional bias. The hiring algorithms would directly inherit societal prejudice when encoding and considering such possibly biased background information. To this end, we call for the reflection on **the right to be a data-driven exception (D3.4)** [10] in the algorithmic hiring scenario. We argue that hiring systems should support individuals' right to be an exception to hiring algorithms, individualizing the hiring decision-making in certain cases. More broadly, we recommend that the hiring pipeline facilitates a more organic human-algorithm collaboration for non-discriminatory hiring decisions rather than enforcing a traditionally linear relationship. For example, there is potential to allow human-drafted open text for **context narrative for data-driven exceptions (D3.5)** as the prior knowledge for automated CV evaluation (similar to using natural language representations to define recommendation [58]). In that case, candidates can make justifications that may alleviate some of the disadvantages caused by structural discrimination. Nonetheless, it is necessary to examine potential backfire effects (e.g., how people might game the system) and develop intervention approaches (e.g., moderators examining the credibility of context narrative).

Table 4. Power imbalance

Fairness Concern	Description	Example
power imbalance between job-seekers and hiring platforms	Power asymmetry between job-seekers and hiring platforms, exhibited in ways such as overwhelming ads, unrelated recommendations, information leakage, nuisance call, etc.	*I've been job searching for a few weeks now, and every day I keep seeing the same roles on LinkedIn because they're "promoted". No matter what page I check, every other listing seems to be a promoted role.*
power imbalance between job-seekers and companies	Power asymmetry between job-seekers and companies, exhibited in ways such as ghosting, unfair rejection reasons, etc.	*I received my rejection email two weeks after they said they'd get back to me, so it ended up being five weeks after my interview—more than double the time they promised. When I asked for feedback, they told me I didn't have enough children's designs in my portfolio (I had two), which was frustrating since they were also hiring for adult books.*
power imbalance between different job-seeking communities	Imbalanced power and information distribution among different communities due to representation bias in rating websites, blogs, etc.	*If you're not receiving this type of generic advice, you're likely getting advice that mainly applies to young white males working in trendy web development roles or Silicon Valley startups.*

4.4 Power Imbalance

We finally captured the power imbalance as a significant topic of job-seekers' fairness concerns in Table 4. It includes three major topics: (1) *Power imbalance between job-seekers and hiring platforms.* Job-seekers noted that recruitment platforms, as the information hub centralizing recruitment-related resources, may sometimes disadvantage (rather than facilitate) job-seekers, such as promoting unrelated job recommendations and leaking job application information to unrelated companies; (2) *Power imbalance between job-seekers and companies.* Some job-seekers expressed concerns about the power asymmetry between job-seekers and companies with the inherent imbalance of job demand and supply. The opacity of the hiring process largely strengthens the perceptions of such power imbalance. For instance, job-seekers widely complained about suddenly losing all communication from the company (ghosting) or receiving rejections without any reason; (3) *Power imbalance between different job-seeking communities.* The imbalanced representation of different job-seeking communities leads to information asymmetry. As a result, online knowledge and experience related to job-seeking are often inapplicable to specific populations. Users' concerns cover broad dimensions of representation bias, including identity (majority vs. minority), occupation (white collar vs. blue collar jobs), and experience (senior vs. entry-level positions). These factors present another source of inequality from a macro perspective.

4.4.1 Design Implications.

Ensuring two-sided fairness in job recommendation. The findings indicate that the power imbalance between job-seekers and hiring platforms might harm user experience and lead to job-seekers' disengagement with the platform. Particularly, recruitment platforms can occasionally put job-seekers at a disadvantage by promoting irrelevant job recommendations and sharing job-seekers' information with unrelated companies. On this note, we suggest **enhancing two-sided fairness (D4.1)** [52, 71] when developing job recommendation models. Two-sided fairness [52, 71] suggests the consideration of both user and item fairness simultaneously, balancing competing interests and promoting justice between different parties. Specific to the job recommendation setting, two-sided fairness ensures not only fair recommendation of job-seekers to recruiters, but also fair recommendation of positions to job-seekers. In fact, job recommendation algorithms are in line with the producer-consumer model similar to most recommendation systems [52]. However, different from most recommendation systems with consumers as the main source of revenue (e.g., ride-hailing and food delivery), hiring companies as job-post producers often wield influence over promotions and can impact the outcomes of job recommendations, making hiring systems prone to producer-centered design. We recommend that researchers meticulously consider such subtle characteristics when tailoring two-sided fairness models for the hiring context.

Enhancing feedback mechanism for the hiring process. The supply and demand relationship of recruitment creates an intrinsic power imbalance between job-seekers and hiring companies. Our findings reveal that such power imbalance manifests in diverse ways. It often puts job-seekers in a passive and disadvantaged position from the perspective of hiring procedure (e.g., suddenly canceled interviews), information (e.g., rejection without reasons), and communication (e.g., ghosting). On this note, we suggest **enhancing the feedback mechanism (D4.2)** for the hiring process as a regulating method. Though hiring tools have increasingly included the company review and rating as a significant component to engage and inform job-seekers (e.g., glassdoor[5] and Kununu[6]), they largely focus on the employment experience such as company culture and compensation, while sometimes overlooking the hiring process. Besides, the company review and rating can be utilized to propagate the reputations of employers [44], as employees have a louder voice than rejected job seekers. It is a promising direction to develop and evaluate feedback mechanisms in job-seeking tools with the affordance of granularity (e.g., distinguishing between hiring stages and AI/human stakeholders), safety (e.g., allowing anonymity), and authenticity (e.g., moderating fake reviews).

Establishing and enforcing basic procedural transparency. Our findings reveal that the power imbalance between recruiters and candidates often exhibits in the way of information asymmetry. For example, candidates perceive unfair treatment when they fail to track the progress of a job application or get informed of the rejection reason. Therefore, we call for the collaboration of policy-makers and recruitment systems to **establish and enforce at least a basic level of procedural transparency (D4.3)** as a countermeasure for the intrinsic recruiter-candidate power imbalance. For instance, it is important for recruitment systems to afford a progress-tracking interface with a transparent time limit for each stage to allow timely progress notifications (instead of ghosting), and afford a rejection-feedback interface to facilitate the communication of rejection reasons (instead of uninformed rejection).

Reconsidering the generalizability of fair hiring. The power imbalance between different job-seeking communities indicates the representation bias in the recruitment ecosystem: most of the job search experience sharing centers on only a limited group of professions, cultures, and regions. Such representation bias has a direct impact on the applicability of job-seeking-related knowledge for underrepresented groups. Therefore, it sheds light on the potential of constructing an inclusive and customized information ecosystem for job-seekers. First, **supporting specialized navigation (D4.4)** might be a promising avenue to facilitate communication among specific groups, e.g., easing the navigation of experience sharing for underrepresented occupations with diversified hashtags and targeted recommendation mechanisms. More broadly, with the influence of representation bias, the development of fair recruitment algorithms is based on narrow data and applied to limited job and identity categories. For example, fair recruitment algorithms may fail to penetrate (and lack consideration of) the blue-collar jobs in the Global South. To this end, it is warranted to promote input fairness for algorithmic hiring, measuring and countering a lack of representation among applicants due to structural biases [21] (e.g., data donation campaigns for underrepresented groups [26]).

[5]https://www.glassdoor.com/
[6]https://www.kununu.com/

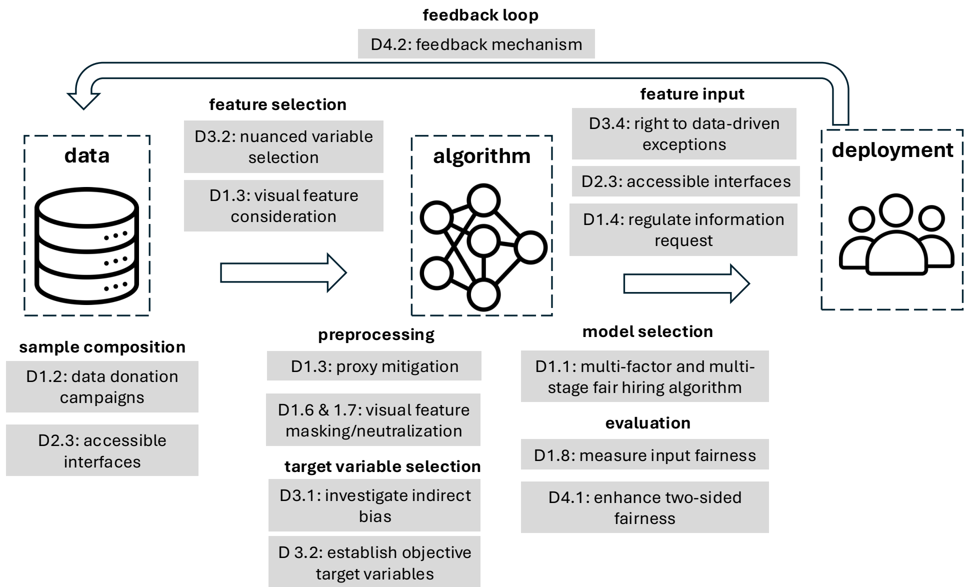


Fig. 2. A framework for designing fair recruitment algorithms

5 FAIR HIRING FRAMEWORK

We finally summarize our research with a fair hiring framework. Taking a user-centric perspective, this framework offers a roadmap for practitioners to bolster fairness in recruitment systems through *algorithm* and *interface* designs.

Figure 2 illustrates the framework for designing fair recruitment algorithms. It considers broad algorithmic design stages during the iterative process of data preparation, algorithm development, and model deployment [21]. We connect our design insights with these algorithmic design stages, such as incorporating *data donation campaigns* for sample composition, *nuanced variable selection* for feature selection, *proxy mitigation* for preprocessing, and *measuring input fairness* for model evaluation.

Figure 3 illustrates the framework for designing fair recruitment interfaces. We contextualize our design insights within different stages in online hiring, including *sourcing, screening, selection, and evaluation*, and also consider design elements at the *ecosystem* level of online hiring systems. Besides, we specify which stakeholder (recruiter or job-seeker) the design element targets.

Note that our framework should serve as a general guide rather than an all-inclusive principle for fair hiring. Some extensively studied dimensions, such as model training based on particular fairness measures, are not covered in this work. Besides, it is significant to assess and address the potential limitations or backfire effects (e.g., decreased efficiency and user engagement with the hiring process) through proof-of-concept systems before large-scale implementation.

6 DISCUSSION

This work presents a comprehensive taxonomy of job seekers' fairness concerns in hiring, based on discourse in an online job community. Building on these insights, we propose a fair hiring framework that incorporates both algorithm and interface design for online recruitment. Overall,

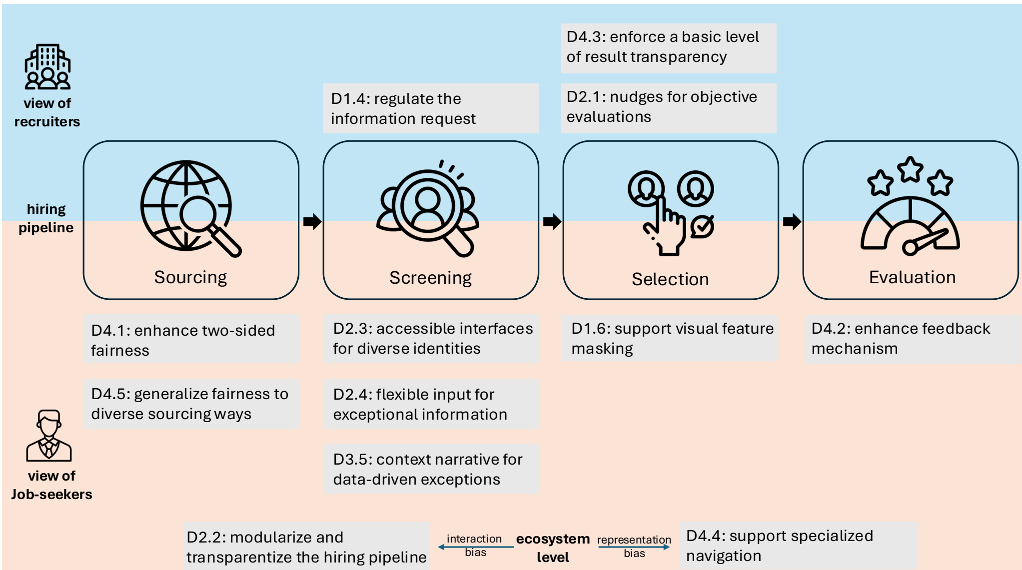


Fig. 3. A framework for designing fair recruitment interfaces

this work contributes to the HCI and responsible computing community by taking a human-centered approach to examining recruitment fairness, bridging the gap between real-world fairness challenges in hiring and practical implications for recruitment system design.

The taxonomy of job seekers' fairness concerns addresses a critical yet often overlooked question: *When developing a fair recruitment system, which fairness objectives should we focus on?* It highlights a range of fairness issues that are important to job seekers but less considered as primary optimization objectives. Regarding *sensitive attributes*, we emphasize a broader set of sensitive variables beyond gender and ethnicity, which are the focus of most fair hiring algorithms [20]. These sensitive variables can be interconnected and manifested through implicit and multi-modal proxies, challenging some existing debiasing strategies that may oversimplify the model [59]. Besides, some attributes have been commonly recognized and protected by non-discrimination laws [14, 49] (e.g., age, sex, ethnicity, disability, and family), and some attributes are not (e.g., appearance and geolocation). We suggest policymakers actively reflect on the public's fairness concerns based on diverse channels such as social media and online communities, which may provide rich insights into refining the anti-discrimination policies and regulations.

We also captured *interaction bias*, where individuals are concerned about differential treatment due to specific interactions with hiring systems and recruiters. This underscores the significance of interactions in fair decision-making, aligning with the current HCI focus on improving design for fair recruitment [40, 80].

Our analysis revealed a noteworthy theme of *improper interpretations of qualifications*, where job seekers questioned the interpretations of commonly accepted hiring criteria such as education and work history. This theme highlights the social construction of discrimination, as in some cases, these "logical" qualifications may perpetuate social inequity and further disadvantage marginalized communities [28, 50].

Finally, we identified the role of *power imbalance* in shaping job seekers' perceptions of fairness, emphasizing the need to contextualize fairness within the broader recruitment ecosystem. This includes acknowledging the power and information asymmetry between candidates and recruiters, as well as the unequal distribution of resources across communities.

The proposed online recruitment framework based on job-seekers' fairness concerns contributes to both algorithm and interface design for fair hiring. The recruitment algorithm framework addresses two key gaps in algorithmic fairness: (1) the use of a single, idealized fairness measure often limits what the algorithm is able to optimize for, preventing generalization to more diverse groups and broader conceptions of fairness [65] (the gap between *fairness conceptualization* and *fairness operationalization*); (2) computational approaches often fail to align mathematical fairness with job seekers' real-world fairness perceptions [37] (the gap between *fairness perception* and *fairness implementation*).

We embed job-seekers' fairness concerns throughout the entire algorithm development pipeline, including sample composition, feature selection, preprocessing, model selection, evaluation, deployment, and feedback loops. From a complementary perspective, the framework for designing a fair recruitment interface aims to enhance hiring fairness in two ways: (1) for recruiters, it seeks to reduce factors contributing to conscious and unconscious human bias in hiring decisions [80]; (2) for job seekers, it aims to minimize latent reasons for perceived unfairness by developing transparent and fair decision-making procedures [38, 66, 75]. This framework offers practical design implications for all stages of hiring that involve the interactions among recruiters, job-seekers, and hiring systems, including sourcing, screening, selection, and evaluation.

However, it is also important to pay attention to the value and incentives motivating different parties in the recruitment market [36]. Companies and job candidates may have conflicting success metrics driven by differing goals and incentives, creating situations that can appear unfair due to differing philosophies between parties, which leads to a systemic gap in fairness perceptions. Therefore, when implementing the fair hiring framework in real-world scenarios, it is crucial to consider the tension between candidate-centered design principles for fair hiring and companies' pursuit of efficiency and profit. For example, removing proxy attributes from CVs to reduce potential biases might raise concerns among hiring experts about losing a holistic perspective on candidates. Policymakers are thus suggested to cautiously consider the feasibility of enforcing specific fair hiring design elements within the sociotechnical contexts.

Overall, we note the need for more human-centered research and value sensitive design into fair hiring, transitioning from idealized computational fairness notions to notions based on concerns raised by the impacted populations [68].

7 LIMITATION

This work has the following limitations. First, we identified job-seekers' concerns based on only r/jobs, one of the largest online job communities on Reddit. With the large community size and no constraints of job-related topics, it covers fairness concerns across different job-seeking stages, and captures considerations of job-seekers in a natural setting. However, it also inherits the limitations of online community analysis, such as representing only those willing (and able) to share job-seeking-related experiences in the community, as well as failing to surface in-depth user perceptions. Therefore, future work based on other human-centered approaches can supplement the understanding job-seekers' fairness concerns for fair hiring design, such as large-scale surveys and in-depth interviews. Besides, Reddit remains a Western-centered platform, with nearly half of its users from the US, which limits the generalizability of this work. On this note, we suggest further work to broadly investigate job-seekers' fairness concerns in other social and cultural settings to enrich the considerations for a fair hiring pipeline. In addition, we adopted a qualitative analysis for the dataset, with identifying notions of fairness concerns as the primary goal. Quantitative analysis, such as investigating proportions and temporal trends of fairness concerns and their correlations with user identities, would further deepen the understanding. Finally, developing a proof-of-concept system would be valuable to assess the feasibility of design implications.

8 CONCLUSION

This study takes a human-centered approach to bridge the gap between real-world fairness challenges in hiring practices and the practical implications for recruitment system design within the HCI and responsible computing community. We first develop a comprehensive taxonomy of job seekers' fairness concerns in hiring from an online job community. This taxonomy reveals issues such as interaction bias, improper interpretations of qualifications, and power imbalances that affect job seekers' perceptions of fairness in the recruitment process – highlighting bias factors often overlooked in fair recruitment system development. Building on the taxonomy, we propose a framework for online recruitment systems, spanning every stage of fair algorithm development and recruitment interface design. In the process, we suggest how practitioners may more generally translate fairness issues raised by job seekers into concrete system designs.

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REFERENCES

[1] Mohsen Abbasi, Sorelle A Friedler, Carlos Scheidegger, and Suresh Venkatasubramanian. 2019. Fairness in representation: quantifying stereotyping as a representational harm. In *Proceedings of the 2019 SIAM International Conference on Data Mining*. SIAM, 801–809.

[2] G Stoney Alder and Joseph Gilbert. 2006. Achieving ethics and fairness in hiring: Going beyond the law. *Journal of Business Ethics* 68 (2006), 449–464.

[3] Neil Anderson. 2011. Perceived job discrimination: Toward a model of applicant propensity to case initiation in selection. *International Journal of Selection and Assessment* 19, 3 (2011), 229–244.

[4] Zinat Ara, Amrita Ganguly, Donna Peppard, Dongjun Chung, Slobodan Vucetic, Vivian Genaro Motti, and Sungsoo Ray Hong. 2024. Collaborative Job Seeking for People with Autism: Challenges and Design Opportunities. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–17.

[5] Lena Armstrong, Jayne Everson, and Amy J Ko. 2023. Navigating a black box: Students' experiences and perceptions of automated hiring. In *Proceedings of the 2023 ACM Conference on International Computing Education Research-Volume 1*. 148–158.

[6] Tara Behrend, Steven Toaddy, Lori Foster Thompson, and David J Sharek. 2012. The effects of avatar appearance on interviewer ratings in virtual employment interviews. *Computers in Human Behavior* 28, 6 (2012), 2128–2133.

[7] Alex Beutel, Jilin Chen, Tulsee Doshi, Hai Qian, Li Wei, Yi Wu, Lukasz Heldt, Zhe Zhao, Lichan Hong, Ed H Chi, et al. 2019. Fairness in recommendation ranking through pairwise comparisons. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*. 2212–2220.

[8] Brandon M Booth, Louis Hickman, Shree Krishna Subburaj, Louis Tay, Sang Eun Woo, and Sidney K D'Mello. 2021. Bias and fairness in multimodal machine learning: A case study of automated video interviews. In *Proceedings of the 2021 international conference on multimodal interaction*. 268–277.

[9] Stephen Cave and Kanta Dihal. 2019. Hopes and fears for intelligent machines in fiction and reality. *Nature machine intelligence* 1, 2 (2019), 74–78.

[10] Sarah H Cen and Manish Raghavan. 2023. The Right to Be an Exception to a Data-Driven Rule. (2023).

[11] Phoebe K Chua and Melissa Mazmanian. 2020. Are you one of us? Current hiring practices suggest the potential for class biases in large tech companies. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2 (2020), 1–20.

[12] Jason A Colquitt and Jessica B Rodell. 2015. Measuring justice and fairness. *The Oxford handbook of justice in the workplace* 1 (2015), 187–202.

[13] Juliet Corbin and Anselm Strauss. 2015. *Basics of qualitative research*. Vol. 14. sage.

[14] U.S. Supreme Court. 1971. Griggs v. Duke Power Co., 401 U.S. 424. https://supreme.justia.com/cases/federal/us/401/424/. Accessed: 2024-08-14.

[15] Cassandra L Crone and Rachel W Kallen. 2022. Interview with an avatar: Comparing online and virtual reality perspective taking for gender bias in STEM hiring decisions. *PloS one* 17, 6 (2022), e0269430.

[16] Maria De-Arteaga, Alexey Romanov, Hanna Wallach, Jennifer Chayes, Christian Borgs, Alexandra Chouldechova, Sahin Geyik, Krishnaram Kenthapadi, and Adam Tauman Kalai. 2019. Bias in bios: A case study of semantic representation bias in a high-stakes setting. In *proceedings of the Conference on Fairness, Accountability, and Transparency*. 120–128.
[17] Tawanna R Dillahunt, Aarti Israni, Alex Jiahong Lu, Mingzhi Cai, and Joey Chiao-Yin Hsiao. 2021. Examining the use of online platforms for employment: A survey of US job seekers. In *Proceedings of the 2021 CHI conference on human factors in computing Systems*. 1–23.
[18] Jessica Maria Echterhoff, Matin Yarmand, and Julian McAuley. 2022. AI-moderated decision-making: Capturing and balancing anchoring bias in sequential decision tasks. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–9.
[19] Shady Elbassuoni, Sihem Amer-Yahia, and Ahmad Ghizzawi. 2020. Fairness of scoring in online job marketplaces. *ACM Transactions on Data Science* 1, 4 (2020), 1–30.
[20] Alessandro Fabris, Nina Baranowska, Matthew J Dennis, Philipp Hacker, Jorge Saldivar, Frederik Zuiderveen Borgesius, and Asia J Biega. 2023. Fairness and bias in algorithmic hiring. *arXiv preprint arXiv:2309.13933* (2023).
[21] Alessandro Fabris, Stefano Messina, Gianmaria Silvello, and Gian Antonio Susto. 2022. Algorithmic fairness datasets: the story so far. *Data Mining and Knowledge Discovery* 36, 6 (2022), 2074–2152.
[22] Sorelle A Friedler, Carlos Scheidegger, and Suresh Venkatasubramanian. 2021. The (im) possibility of fairness: Different value systems require different mechanisms for fair decision making. *Commun. ACM* 64, 4 (2021), 136–143.
[23] Batya Friedman. 1996. Value-sensitive design. *interactions* 3, 6 (1996), 16–23.
[24] Radhika Garg, Yash Kapadia, and Subhasree Sengupta. 2021. Using the lenses of emotion and support to understand unemployment discourse on Reddit. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–24.
[25] Sahin Cem Geyik, Stuart Ambler, and Krishnaram Kenthapadi. 2019. Fairness-aware ranking in search & recommendation systems with application to linkedin talent search. In *Proceedings of the 25th acm sigkdd international conference on knowledge discovery & data mining*. 2221–2231.
[26] Alejandra Gomez Ortega, Jacky Bourgeois, Wiebke Toussaint Hutiri, and Gerd Kortuem. 2023. Beyond data transactions: a framework for meaningfully informed data donation. *AI & SOCIETY* (2023), 1–18.
[27] Nina Grgic-Hlaca, Muhammad Bilal Zafar, Krishna P Gummadi, and Adrian Weller. 2016. The case for process fairness in learning: Feature selection for fair decision making. In *NIPS symposium on machine learning and the law*, Vol. 1. Barcelona, Spain, 11.
[28] Anikó Hannák, Claudia Wagner, David Garcia, Alan Mislove, Markus Strohmaier, and Christo Wilson. 2017. Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr. In *Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing*. 1914–1933.
[29] Moritz Hardt, Eric Price, and Nati Srebro. 2016. Equality of opportunity in supervised learning. *Advances in neural information processing systems* 29 (2016).
[30] Marc P Hauer, Johannes Kevekordes, and Maryam Amir Haeri. 2021. Legal perspective on possible fairness measures–a legal discussion using the example of hiring decisions. *Computer Law & Security Review* 42 (2021), 105583.
[31] Leo Hemamou and William Coleman. 2022. Delivering fairness in human resources ai: Mutual information to the rescue. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 867–882.
[32] Léo Hemamou, Arthur Guillon, Jean-Claude Martin, and Chloé Clavel. 2021. Don't judge me by my face: An indirect adversarial approach to remove sensitive information from multimodal neural representation in asynchronous job video interviews. In *2021 9th International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 1–8.
[33] Shenggang Hu, Jabir Alshehabi Al-Ani, Karen D Hughes, Nicole Denier, Alla Konnikov, Lei Ding, Jinhan Xie, Yang Hu, Monideepa Tarafdar, Bei Jiang, et al. 2022. Balancing gender bias in job advertisements with text-level bias mitigation. *Frontiers in big Data* 5 (2022), 805713.
[34] Patrick Kline, Evan K Rose, and Christopher R Walters. 2022. Systemic discrimination among large US employers. *The Quarterly Journal of Economics* 137, 4 (2022), 1963–2036.
[35] Max Langenkamp, Allan Costa, and Chris Cheung. 2020. Hiring fairly in the age of algorithms. *arXiv preprint arXiv:2004.07132* (2020).
[36] Mitra Lashkari and Jinghui Cheng. 2023. "Finding the Magic Sauce": Exploring Perspectives of Recruiters and Job Seekers on Recruitment Bias and Automated Tools. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16.
[37] Maude Lavanchy, Patrick Reichert, Jayanth Narayanan, and Krishna Savani. 2023. Applicants' fairness perceptions of algorithm-driven hiring procedures. *Journal of Business Ethics* 188, 1 (2023), 125–150.
[38] Min Kyung Lee, Anuraag Jain, Hea Jin Cha, Shashank Ojha, and Daniel Kusbit. 2019. Procedural justice in algorithmic fairness: Leveraging transparency and outcome control for fair algorithmic mediation. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–26.

[39] Barbara Leporini, Marina Buzzi, and Marion Hersh. 2023. Video conferencing tools: Comparative study of the experiences of screen reader users and the development of more inclusive design guidelines. *ACM Transactions on Accessible Computing* 16, 1 (2023), 1–36.

[40] Weiwen Leung, Zheng Zhang, Daviti Jibuti, Jinhao Zhao, Maximilian Klein, Casey Pierce, Lionel Robert, and Haiyi Zhu. 2020. Race, gender and beauty: The effect of information provision on online hiring biases. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–11.

[41] Lan Li, Tina Lassiter, Joohee Oh, and Min Kyung Lee. 2021. Algorithmic hiring in practice: Recruiter and HR Professional's perspectives on AI use in hiring. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*. 166–176.

[42] Louis Lippens. 2024. Computer says 'no': Exploring systemic bias in ChatGPT using an audit approach. *Computers in Human Behavior: Artificial Humans* 2, 1 (2024), 100054.

[43] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).

[44] Ioana Marinescu, Andrew Chamberlain, Morgan Smart, and Nadav Klein. 2021. Incentives can reduce bias in online employer reviews. *Journal of Experimental Psychology: Applied* 27, 2 (2021), 393.

[45] Mary L McHugh. 2012. Interrater reliability: the kappa statistic. *Biochemia medica* 22, 3 (2012), 276–282.

[46] Miroslava Migovich, Deeksha Adiani, Michael Breen, Amy Swanson, Timothy J Vogus, and Nilanjan Sarkar. 2024. Stress Detection of Autistic Adults during Simulated Job Interviews Using a Novel Physiological Dataset and Machine Learning. *ACM Transactions on Accessible Computing* 17, 1 (2024), 1–25.

[47] Varun Nagaraj Rao and Aleksandra Korolova. 2023. Discrimination through Image Selection by Job Advertisers on Facebook. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*. 1772–1788.

[48] Preetam Nandy, Cyrus Diciccio, Divya Venugopalan, Heloise Logan, Kinjal Basu, and Noureddine El Karoui. 2022. Achieving Fairness via Post-Processing in Web-Scale Recommender Systems. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. 715–725.

[49] Council of the European Union. 2000. Council Directive 2000/43/EC Implementing the Principle of Equal Treatment Between Persons Irrespective of Racial or Ethnic Origin. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=%20celex%3A32000L0043. Accessed: 2024-08-14.

[50] Tracy E Ore and Paul Kurtz. 2000. *The social construction of difference and inequality*. Mayfield Publishing.

[51] Prasanna Parasurama and João Sedoc. 2021. Degendering Resumes for Fair Algorithmic Resume Screening. *arXiv preprint arXiv:2112.08910* (2021).

[52] Gourab K Patro, Arpita Biswas, Niloy Ganguly, Krishna P Gummadi, and Abhijnan Chakraborty. 2020. Fairrec: Two-sided fairness for personalized recommendations in two-sided platforms. In *Proceedings of the web conference 2020*. 1194–1204.

[53] Alejandro Pena, Ignacio Serna, Aythami Morales, and Julian Fierrez. 2020. Bias in multimodal AI: Testbed for fair automatic recruitment. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*. 28–29.

[54] J Pfeffer. 1998. The human equation: Building profits by putting people first. *Harvard Business School* (1998).

[55] Nicholas Proferes, Naiyan Jones, Sarah Gilbert, Casey Fiesler, and Michael Zimmer. 2021. Studying reddit: A systematic overview of disciplines, approaches, methods, and ethics. *Social Media+ Society* 7, 2 (2021), 20563051211019004.

[56] Sharon L Segrest Purkiss, Pamela L Perrewé, Treena L Gillespie, Bronston T Mayes, and Gerald R Ferris. 2006. Implicit sources of bias in employment interview judgments and decisions. *Organizational Behavior and Human Decision Processes* 101, 2 (2006), 152–167.

[57] Lincoln Quillian, Devah Pager, Ole Hexel, and Arnfinn H Midtbøen. 2017. Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences* 114, 41 (2017), 10870–10875.

[58] Filip Radlinski, Krisztian Balog, Fernando Diaz, Lucas Dixon, and Ben Wedin. 2022. On natural language user profiles for transparent and scrutable recommendation. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2863–2874.

[59] Manish Raghavan, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 469–481.

[60] Peter A Riach and Judith Rich. 2002. Field experiments of discrimination in the market place. *The economic journal* 112, 483 (2002), F480–F518.

[61] Jazz Rui Xia Ang, Ping Liu, Emma McDonnell, and Sarah Coppola. 2022. "In this online environment, we're limited": Exploring Inclusive Video Conferencing Design for Signers. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. 1–16.

[62] Clara Rus, Jeffrey Luppes, Harrie Oosterhuis, and Gido H Schoenmacker. 2022. Closing the gender wage gap: Adversarial fairness in job recommendation. *arXiv preprint arXiv:2209.09592* (2022).

[63] Abel Salinas, Parth Shah, Yuzhong Huang, Robert McCormack, and Fred Morstatter. 2023. The unequal opportunities of large language models: Examining demographic biases in job recommendations by chatgpt and llama. In *Proceedings of the 3rd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization*. 1–15.

[64] Javier Sánchez-Monedero, Lina Dencik, and Lilian Edwards. 2020. What does it mean to'solve'the problem of discrimination in hiring? Social, technical and legal perspectives from the UK on automated hiring systems. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 458–468.

[65] Priya Sarkar and Cynthia CS Liem. 2024. " It's the most fair thing to do but it doesn't make any sense": Perceptions of Mathematical Fairness Notions by Hiring Professionals. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW1 (2024), 1–35.

[66] Avital Shulner-Tal, Tsvi Kuflik, and Doron Kliger. 2023. Enhancing fairness perception–Towards human-centred AI and personalized explanations understanding the factors influencing laypeople's fairness perceptions of algorithmic decisions. *International Journal of Human–Computer Interaction* 39, 7 (2023), 1455–1482.

[67] John D Skrentny. 2006. Policy-elite perceptions and social movement success: Understanding variations in group inclusion in affirmative action. *Amer. J. Sociology* 111, 6 (2006), 1762–1815.

[68] Megha Srivastava, Hoda Heidari, and Andreas Krause. 2019. Mathematical notions vs. human perception of fairness: A descriptive approach to fairness for machine learning. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*. 2459–2468.

[69] stuck_in_the_matrix; Watchful1; RaiderBDev. 2024. Reddit comments/submissions 2005-06 to 2023-12. (2024).

[70] Hung-Yue Suen and Kuo-En Hung. 2023. Comparing job applicant deception in asynchronous vs synchronous video interviews, with and without AI-assisted assessments. *Information Technology & People* (2023).

[71] Tom Sühr, Asia J Biega, Meike Zehlike, Krishna P Gummadi, and Abhijnan Chakraborty. 2019. Two-sided fairness for repeated matchings in two-sided markets: A case study of a ride-hailing platform. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 3082–3092.

[72] Tom Sühr, Sophie Hilgard, and Himabindu Lakkaraju. 2021. Does fair ranking improve minority outcomes? understanding the interplay of human and algorithmic biases in online hiring. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*. 989–999.

[73] Akshaj Kumar Veldanda, Fabian Grob, Shailja Thakur, Hammond Pearce, Benjamin Tan, Ramesh Karri, and Siddharth Garg. 2023. Are Emily and Greg still more employable than Lakisha and Jamal? Investigating algorithmic hiring bias in the era of ChatGPT. *arXiv preprint arXiv:2310.05135* (2023).

[74] Piaohong Wang, Siying Hu, Bo Wen, and Zhicong Lu. 2024. "There is a Job Prepared for Me Here": Understanding How Short Video and Live-streaming Platforms Empower Ageing Job Seekers in China. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–14.

[75] Ruotong Wang, F Maxwell Harper, and Haiyi Zhu. 2020. Factors influencing perceived fairness in algorithmic decision-making: Algorithm outcomes, development procedures, and individual differences. In *Proceedings of the 2020 CHI conference on human factors in computing systems*. 1–14.

[76] Bernard Weiner, Irene Frieze, Andy Kukla, Linda Reed, Stanley Rest, and Robert M Rosenbaum. 1987. Perceiving the causes of success and failure.. In *Preparation of this paper grew out of a workshop on attribution theory held at University of California, Los Angeles, Aug 1969*. Lawrence Erlbaum Associates, Inc.

[77] Bernard Weiner and Jack Sierad. 1975. Misattribution for failure and enhancement of achievement strivings. *Journal of Personality and Social Psychology* 31, 3 (1975), 415.

[78] Wikipedia. 2024. 2023 Reddit API controversy. https://en.wikipedia.org/wiki/2023_Reddit_API_controversy. Accessed: 2024-09-12.

[79] Maya Yaneva. 2018. Employee satisfaction vs. employee engagement vs. employee NPS. *European Journal of Economics and Business Studies* 4, 1 (2018), 221–227.

[80] Mingzhe Yang, Hiromi Arai, Naomi Yamashita, and Yukino Baba. 2024. Fair Machine Guidance to Enhance Fair Decision Making in Biased People. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–18.

[81] Lixuan Zhang and Christopher Yencha. 2022. Examining perceptions towards hiring algorithms. *Technology in Society* 68 (2022), 101848.

[82] Zhaowei Zhu, Yuanshun Yao, Jiankai Sun, Hang Li, and Yang Liu. 2023. Weak proxies are sufficient and preferable for fairness with missing sensitive attributes. In *International Conference on Machine Learning*. PMLR, 43258–43288.